6-2003

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DOI: https://doi.org/10.1111/1468-5957.05443

Published in Journal of Business Finance and Accounting, 2003, 30 (5), 749-769.
https://doi.org/10.1111/1468-5957.05443

The Quality of Analysts' Earnings Forecasts During the Asian Crisis: Evidence from Singapore

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1. INTRODUCTION

It is now generally accepted that earnings forecasts issued by financial analysts form an important input in the valuation of firms by market participants. Prior studies that examine the efficiency of these forecasts, however, find that they suffer from certain systematic errors. For example, one of the most widely documented errors is the tendency of analysts to issue forecasts that are systematically optimistic, that is, forecasts that are systematically higher than the actual earnings (see, for example, O'Brien, 1988; Stickel, 1990; and Kang, O'Brien and Sivaramakrishnan, 1994). Furthermore, analysts forecast changes in earnings (whether positively or negatively signed) that are larger in magnitude than the actual changes (De Bondt and

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Thaler, 1990). Finally, analysts in the US appear to underreact (overreact) to bad (good) news (Easterwood and Nutt, 1999).

It remains an open question, however, as to what factors induce the alleged inefficiencies in analysts' forecasts. One persuasive explanation is that forecast biases are rational outcomes of specific incentives that analysts face (Francis and Philbrick, 1993). For example, Das, Levine and Sivaramakrishnan (1998) and Lim (2001) argue that analysts introduce an optimistic bias in their forecasts to improve relations with corporate management and ensure access to private information. To provide empirical support for this assertion, the authors examine the cross-sectional variation in forecast biases. They assert that earnings for companies with greater informational uncertainty are harder to predict, and therefore analysts have a greater need for access to managers of such companies. Similarly, managers of poorly performing companies would be less forthcoming in disclosing information, and hence analysts would need to establish better relations with such companies.[1] The biases in earnings forecasts would, thus, be an increasing function of (1) greater informational uncertainty and (2) poorer performance of the companies being covered. Lim (2001) finds evidence that supports both these predictions.[2]

An alternative explanation of forecast biases draws upon the literature on behavioural finance. Such a view treats a forecast as the outcome of a decision-making process in which an analyst combines the available fundamental information with his personal judgement, which is likely to suffer from the same cognitive biases as those of investors at large. De Bondt and Thaler (1990), for example, argue that the over-estimation of earnings changes by analysts is explained by the representativeness heuristic (Kahneman and Tversky, 1973). More recently, Daniel, Hirshleifer and Subrahmanyam (1998) model the over or under-reaction of investors as a direct result of their cognitive biases in information processing. These biases are likely to be accentuated for diffuse tasks which require judgement than for mechanical tasks which provide immediate feedback. This view suggests that the predictable cross-sectional variation in forecast biases uncovered by Das et al. (1998) and Lim (2001) can be explained behaviourally. Making forecasts for companies with greater informational uncertainty demand a more prominent role for human judgement, thereby escalating the potential for judgemental biases. Hence, contrary to the claims of Das et al. (1998) and Lim (2001), predictable cross-sectional increase in forecast biases for companies with greater informational uncertainty could also be rationalised by a behavioural explanation.

In contrast to the existing cross-sectional studies, our paper examines the temporal variation in forecast biases. We first draw upon three disparate strands of literature to develop a comprehensive empirical framework to examine the efficiency of analysts' forecasts in Singapore. We then use this framework to compare the efficiency of analysts' forecasts issued during the crisis period to that of forecasts made in the pre-crisis 'normal' period. Our special interest in the crisis period stems from the observation that by its very definition, the crisis period had the two characteristics, increased uncertainty and poorer corporate performance, that according to the existing cross-sectional studies accentuate forecast biases.

The Asian crisis hit the region in early July 1997, starting with the depreciation of the Thai Baht on 2 July, 1997.[3] We separate the forecasts made by analysts after the onset of the crisis (in the period July 1997–1999) from those made during the pre-crisis period of January 1990 to June 1997. Using these dates ensure that issuers of crisis period forecasts already had the knowledge of the crisis before issuing those forecasts. So, any inefficiency found in the forecasts cannot be attributed to the fact that the crisis itself was unexpected for most of the market participants. This study focuses on Singapore as it has better quality data available for analysts' forecasts than other Southeast Asian countries more affected by the crisis like Indonesia and Malaysia.[4]

By comparing forecast inefficiencies across two periods, we seek to achieve two objectives. First, such an analysis could help us better discriminate the two competing explanations for the observed forecast biases. If forecasts made during the crisis period were to suffer more from systematic biases, it would be consistent with the behavioural explanation, as cognitive biases are likely to exacerbate during the highly uncertain crisis period when more human judgement is needed to issue earnings forecasts. In contrast, there is no compelling reason to expect that agency concerns of analysts would escalate during the crisis time. Second, it is important to know the degree of efficiency of earnings forecasts during periods of heightened uncertainty, as these are precisely the times when good forecasts have the highest value.

The rest of the paper is organised as follows. In Section 2 we review the previous literature to identify three notions of the efficiency of analysts' forecasts, and outline our research design. In Section 3, we describe our data, and report our results. Finally, Section 4 concludes the paper.

2. RESEARCH DESIGN

The extant literature contains three distinct notions of the efficiency of analysts' forecasts. Each of these notions appears to be associated with a separate strand of literature. We bring together these literatures to identify tests of forecast efficiency that we, in Section 3, employ to examine the forecasts made during pre and post-crisis periods.

(i) Optimism in Forecasts

The simplest and most tested notion of efficiency is that forecasted earnings should not be systematically higher or lower than subsequently realised actual earnings. Let us define forecast error as follows:

$$\mathrm{FE}_t = \frac{E_t - F_t^{t-1}}{P} \tag{1}$$

where E_t is the actual earnings for a firm in year t, and F_t^{t-1} is the consensus forecast of the firms's year t earnings made at year $t-1$. Denominator P is the contemporaneous stock price at the time of forecast that is used to scale the forecast errors to control for the cross-sectional differences. Negative (positive) values of errors in equation (1) imply that analysts issue forecasts that exceed (fall below) subsequently realised earnings. If analysts' forecasts were efficient, the forecast errors in equation (1) averaged across companies would not statistically deviate from zero.

(ii) Extremism in Forecasted Change

The second notion of forecast efficiency relates to forecasted changes in earnings. It differs from the first analysis in that it is concerned with forecasted *changes* in earnings rather than forecasted *amounts* (De Bondt and Thaler, 1990). If analysts were to exhibit extremism, they will forecast changes in earnings (whether positively or negatively signed) that are larger in absolute magnitude than the actual changes. Following De Bondt and Thaler (1990), we run the following model to test this view of efficiency:

$$\mathrm{AC}_t = \alpha + \beta \mathrm{FC}_t + \varepsilon_t. \tag{2}$$

This is essentially a regression of actual change against forecasted change to test the null hypothesis: $(\alpha, \beta) = (1, 0)$, against the alternative: $(\alpha, \beta) \neq (1, 0)$. Actual earnings change, $\mathrm{AC}_t = (E_t - E_{t-1})/P$, is the actual current year earnings change scaled by the stock price at $t-1$. Forecasted change, FC_t is simply $(F_t^{t-1} - E_{t-1})/P$. If analysts in Singapore systematically overestimate changes in earnings, β will be significantly less than one, signifying that analysts' forecasts are characterised by extremism.

(iii) Optimal Reaction to News

Finally, the third notion of forecast efficiency implies that analysts should incorporate all earnings related news in a timely manner and without bias into their forecasts.[5] This dimension of forecast efficiency does not require analysts to be accurate all the times, but rather that their errors should not vary predictably with any identifiable earnings-related information. To test this notion, Abarbanell and Bernard (1992) define a subset of earnings related news – the prior-year's earnings change, and test whether forecast errors can be predicted using this variable. They estimate the following equation using data from the US:

$$\mathrm{FE}_t = \gamma_0 + \gamma_1 \mathrm{PERF}_{t-1} + \varepsilon_t \tag{3}$$

where prior-year earnings change, $\mathrm{PERF}_{t-1} = (E_{t-1} - E_{t-2})/P$, is the variable employed as a proxy for news. If analysts were efficient in incorporating prior-year earnings news into their forecasts, then the coefficient $\gamma_1 = 0$. If analysts underreact (overreact) to prior-year earnings change, γ_1 would be positive (negative).

Before making definite conclusions on this generalised underreaction to news, however, one needs to allow for the possibility that analysts' interpretation of news is contingent upon the nature of the type of news (Easterwood and Nutt, 1999). To do so, we follow the procedure in Easterwood and Nutt (1999). Firms are first grouped based on whether their past performance has been bad, normal or good. This is to identify potential implications of different prior-year performance on current earnings. Equation (3) above can thus be expanded as follows:

$$\frac{F_t^{t-1} - E_{t-1}}{P} = \alpha_0 + \alpha_1 \mathrm{LOPERF}_{t-1} + \alpha_2 \mathrm{HIPERF}_{t-1} + \alpha_3 \mathrm{PERF}_{t-1} + \alpha_4(\mathrm{PERF}_{t-1} \times \mathrm{LOPERF}_{t-1}) + \alpha_5(\mathrm{PERF}_{t-1} \times \mathrm{HIPERF}_{t-1}) + \varepsilon_t. \tag{4}$$

Within each year, firms are ranked according to the magnitude of their PERF_{t-1} values. The top quartile firms are considered to be high performers, and bottom quartile, low performers. Firms lying in the middle two quartiles are regarded as normal performers. HIPERF_{t-1} is a dummy variable which returns a value of '1' when the firm's performance is in the higher quartile, and '0' if otherwise. Similarly, LOPERF_{t-1} is coded '1' when the firm's performance is in the lower quartile and '0' if otherwise. The slope coefficient α_3 measures the forecasted impact of prior-year performance for the middle two quartiles. The combined slope coefficients $(\alpha_3 + \alpha_4)$ and $(\alpha_3 + \alpha_5)$ measure the forecasted impact of prior performance for the lower and upper quartile respectively. Intercept coefficients are interpreted in a similar manner.

Equation (4) models analysts' forecasts of earnings change as a function of the nature of prior-year performance. Following this, we compare a similar model of *actual* earnings change as a function of prior-year performance:

$$\frac{E_t - E_{t-1}}{P} = \alpha_0 + \alpha_1 \mathrm{LOPERF}_{t-1} + \alpha_2 \mathrm{HIPERF}_{t-1} + \alpha_3 \mathrm{PERF}_{t-1} + \alpha_4(\mathrm{PERF}_{t-1} \times \mathrm{LOPERF}_{t-1}) + \alpha_5(\mathrm{PERF}_{t-1} \times \mathrm{HIPERF}_{t-1}) + \varepsilon_t. \tag{5}$$

Notice that the dependent variable is now *actual* earnings change instead of *forecasted* earnings change. A comparison of these two models will tell us if analysts have incorporated efficiently the information in prior-year earnings. Equation (6), depicted below, is derived by subtracting equation (4) from equation (5):

$$\begin{aligned}\frac{E_t - F_t^{t-1}}{P} = {} & \alpha_0 + \alpha_1 \mathrm{LOPERF}_{t-1} + \alpha_2 \mathrm{HIPERF}_{t-1} + \alpha_3 \mathrm{PERF}_{t-1} \\ & + \alpha_4 (\mathrm{PERF}_{t-1} \times \mathrm{LOPERF}_{t-1}) + \alpha_5 (\mathrm{PERF}_{t-1} \\ & \times \mathrm{HIPERF}_{t-1}) + \varepsilon_t. \qquad (6)\end{aligned}$$

If analysts' forecasts are based on the same parameters as the actual process that generates them, then the forecast error regression should have insignificant coefficients and no explanatory power. If however, analysts are inefficient in incorporating earnings-relevant information, then the forecast error regression would be explanatory. If Abarbanell and Bernard's (1992) findings of under-reaction hold for all three classifications of prior performance, then all the slope coefficients should be positive. If analysts' responses are characterised by over-reaction, then the slope coefficients should be negative. Finally, if analysts are systematically optimistic (under-reacting to bad news *and* over-reacting to good news), as reported by Easterwood and Nutt (1999), the combined coefficient of $(\alpha_3 + \alpha_4)$ will be positive and $(\alpha_3 + \alpha_5)$ negative.

Our methodology has hitherto employed prior-year earnings change (PERF_{t-1}) as a proxy for earnings related news. However, as pointed out by Easterwood and Nutt (1999), one possible weakness of using PERF_{t-1} is that the magnitude of prior-year earnings change may include both an expected and unexpected component. If we focus only on the raw earnings change, we may understate the inefficiency of analysts' forecasts. This problem can be mitigated by using *unexpected* prior-year earnings change, termed as UPERF_{t-1}, as the explanatory variable (Easterwood and Nutt, 1999). UPERF_{t-1} is simply PERF_{t-1} minus the firm's average earnings change over the preceding three years (from $t-2$ to $t-4$), scaled by their respective stock prices. The resulting reformulation of equations (4) to (6) replaces PERF_{t-1} with UPERF_{t-1} as a news proxy.[6]

In the next section, we estimate the above models of forecast efficiency separately for the pre and post-crisis periods to detect potential differences in analysts' forecasting ability during periods of heightened economic uncertainty.

3. DATA AND RESULTS

We obtain our data from Institutional Brokers Estimates Systems (I/B/E/S) International Inc. I/B/E/S collects earnings estimates for listed firms that command sufficient institutional interest. Defining the consensus forecast as the median forecast where there are *at least four* analysts making earnings estimates (Elliot, Philbrick and Weidman, 1995), we select eight-month ahead forecasts as representative forecasts for year t's earnings (Easterwood and Nutt, 1999). This horizon ensures that analysts have the past year's ($t-1$) annual report, and thus the previous year's earnings figures, available to them when they make their forecasts. It also takes into account the problem of stale forecasts on I/B/E/S, highlighted by past research (O'Brien, 1988; and De Bondt and Thaler, 1990).[7] In addition, a firm is only included in our sample if it has at least six consecutive years of actual annual earnings data (t to $t-5$). Finally, we also require the firm's stock price P at the time of the forecast, available from Datastream, for scaling our variables to control for heteroscedasticity. All resulting variables of interest are denominated in Singapore dollars (SGD). Conversions, using the appropriate exchange rates, are made when necessary. The average month-end SGD/USD and SGD/GBP exchange rates in our sample period are US$0.6282 and £0.3812 respectively.

In Singapore, I/B/E/S's records of forecasts data begin in 1987 whilst actual earnings figures go as far back as 1985. The selection criteria eventually yield a sample of 601 firm-year observations spanning from 1990 to 1999 (henceforth referred to as the main sample). We then partition the main sample into pre and post-crisis sub samples. We expect the post-crisis sample to be smaller as it spans only two years (mid 1997–1999). This, however, is mitigated somewhat by the increasing firm coverage by I/B/E/S through the years. The eventual pre post-crisis samples consist of 494 and 107 firm-years respectively. We note that just prior to the crisis, our included firms derived an average of 83.2% of their total sales from Asia including Singapore.[8] Considering this exposure, analysts issuing earnings forecasts for such firms after the onset of the crisis will need to factor in the relevant implications of the crisis.

Table 1 lists the characteristics of the main sample. In Panel A, we show the sample representation as a function of firm, industry and year. The number of selected firms is 111, with each firm represented an average (median) of 5 (6) times. By industry, there were a total of 33 industries (as coded by I/B/E/S) represented with a mean (median) of 24 (25) industries represented in each year. Finally, in the ten years represented, each year contained a mean

Table 1

Sample Descriptives

Panel A: Sample Representation as a Function of Firm, Industry and Year

		Number of Times Represented				
Representation by:	*Total*	*Min.*	*Max.*	*Mean*	*Median*	*Std. Dev.*
Firm	111	1	10	5	6	3.04
Industry (IBES code)	33	5	30	24	25	7.20
Year	10	6	83	60	70	24.00

Panel B: Sample Distribution and Firm Size

Year	*No. of Firms*	*Average Assets (S$m)*	*Average Market Value (S$m)*
1990	32	n.a.	1,114
1991	53	n.a.	1,026
1992	56	2,335	1,055
1993	67	3,119	1,619
1994	72	3,322	1,524
1995	75	3,599	1,564
1996	78	4,114	1,457
1997	79	4,741	1,118
1998	83	5,356	1,460
1999	6	2,078	1,068
Overall	601	3,583	1,300

Notes:
The sample consists of 601 firm-year observations that had eight-month ahead consensus earnings forecasts, and at least six consecutive years of actual earnings available from I/B/E/S. *Average assets* refer to the mean total assets (book value) of firms in that particular year, denominated in Singapore dollars. In the same manner, *average market value* is the average market value of included firms' equity in that year.

(median) of 60 (70) firms. In Panel B, we present details of the sample distribution and firm size by year. From the firm-years column, we observe that the number of firms followed is steadily increasing since 1990. This we can ascribe to the increasing number of firm forecasts data collected by I/B/E/S over the years. For 1999, only early observations are available but we included them to give us the maximum possible sample representation for the post-crisis analysis. Panel B also gives us information of the size of the average firm according to its book value of total assets and market value of equity. Across the years, though there is a slight increasing trend for average assets, the representative firm's average market value has remained relatively stable.

(i) Optimism in Forecasts

To investigate the extent of optimism in analysts' forecasts across the pre and post-crisis periods, we calculate average forecast errors for each year of our sample period. The results are reported in Table 2. All except one of the forecast errors are negatively signed, with four of them being significant. Testing for the entire sample of ten years, the resultant forecast error as a percentage of price is -1.29 ($t = -5.87$). It is also worthwhile for us to note that our median forecast error is negative for seven out of ten years. Our results seem consistent with the extant literature, suggesting that analysts display excessive optimism. However, we notice that in the years 1997 and 1998, analysts appear to exhibit larger magnitudes of optimism compared to the earlier years. Bearing in mind that the crisis began in 1997, this suggests that analysts committed greater errors during the post-crisis period.

(ii) Extremism in Forecasted Change

Moving on to the second notion of efficiency, we examine for similar discriminatory evidence surrounding the pre and post-crisis periods. First, we report the main sample regression results in Panel A of Table 3. Interestingly, our regression coefficients bear a striking resemblance to De Bondt and Thaler's (1990) in that the slope coefficient β is significantly below

Table 2

Forecast Errors by Year

Year	*No. of Firms*	*Forecasts Error as a Percentage of Price*			
		Mean	*Median*	*Std. Dev.*	*t–stat on Mean*
1990	32	−0.83	−0.18	2.31	−2.03
1991	53	−0.39	−0.44	2.97	−0.96
1992	56	−0.08	0.00	2.58	−0.25
1993	67	0.42	0.52	4.14	0.83
1994	72	−0.65*	0.00	2.62	−2.10
1995	75	−0.17	−0.53	6.91	−0.22
1996	78	−0.62*	−0.24	2.09	−2.60
1997	79	−2.57**	−1.49	5.00	−4.57
1998	83	−5.22**	−2.12	9.13	−5.21
1999	6	−1.35	−0.31	4.79	−0.69
Overall	601	−1.29**	−0.59	5.39	− 5.87

Notes:
The sample consists of 601 firm-year observations that had eight-month ahead consensus earnings forecasts, and at least six consecutive years of actual earnings available from I/B/E/S. Forecasts errors are presented here as a percentage of price, defined as:

$$\mathrm{FE}_t = \frac{E_t - F_t^{t-1}}{P} \times 100\%$$

where E_t is the actual reported earnings for year t, F_t^{t-1} is the forecast of year t's earnings made eight months prior to year end, and P is the stock price at the time of forecast. ** and * indicates a significance from zero at the 0.01 and 0.05 levels respectively.

one (0.639, $t = -10.804$). This signifies that the actual earnings changes averaged only 64% of the forecasted earnings changes, indicating extremism in analysts' forecasts of earnings changes.

Upon closer examination of the sub samples in Panel B, however, we fail to find evidence of extremism in the pre-crisis period. The pre-crisis slope coefficient is observed to be insignificantly different from one (0.981 $t = -0.125$), showing that analysts were actually efficient in forecasting changes in earnings for companies before the crisis. The strength of regression ($R^2 = 0.410$, $F = 342.217$) corroborates this. In contrast, the post-crisis regression is not significant with $R^2 = 0.000$ ($F = 0.0351$), implying that actual changes in earnings were *independent* from analysts' forecasted changes.

The increased uncertainty during the crisis period, thus, appears to be associated with analysts exhibiting systematic extremism that was absent during the pre-crisis period. This

Table 3

Regression of Actual Earnings Change on Forecasted Change

Sample	*Intercept*	*Slope*	R^2	*F Stat*
Panel A: Main Sample				
Our main sample	**−0.010****	**0.639****	**0.163**	**116.713****
	(−4.437)	(−10.804)		
De Bondt and Thaler's sample[1]	**−0.094****	**0.648****	**0.217**	**n.a.**
	(−3.70)	(−21.7)	(Adjusted R^2)	
Panel B: Pre and Post-crisis Sub Samples				
Pre-crisis	**−0.005****	**0.981**	**0.410**	**342.217****
	(−2.687)	(−0.125)		
Post-crisis	**−0.034****	**0.028****	**0.000**	**0.035**
	(−4.429)	(−6.359)[2]		

Notes:
This table presents the parameter estimates for the model:

$$\mathrm{AC}_t = \alpha + \beta \mathrm{FC}_t + \varepsilon_t.$$

Actual earnings change, AC_t, is given by $(E_t - E_{t-1})/P$, which is forecasted change scaled by price at $t-1$. Forecasted change, FC_t, is given by $(F_t^{t-1} - E_{t-1})/P$, where F_t^{t-1} is the forecast of year t's earnings made at $t-1$ (eight-month ahead). t-statistics for the intercept and slope are reported in parentheses beneath the coefficient estimates. The null hypothesis tested is: $(\alpha, \beta) = (0, 1)$. Our main sample consists of 601 firm-year observations that had eight-month ahead consensus earnings forecasts, and at least six consecutive years of actual earnings available from I/B/E/S. ** and * indicates that the coefficient is significantly different from *the tested null hypotheses* at the 0.01 and 0.05 levels respectively.

1. We note that De Bondt and Thaler (1990) scaled the regression variables by the standard deviation of earnings per share between years $t-10$ to $t-2$, whilst we scale these variables by price.
2. Though the post-crisis slope of 0.028 is significantly different from one ($t = -6.359$), it is *not* significantly different from zero. This is consistent with the observed non-explanatory R^2 of 0.000 ($F = 0.035$)

adds credit to the view that behavioural factors, rather than agency concerns, are more salient in causing biases in analysts' forecasts. Interestingly, our evidence also mirrors the cross sectional differences in forecast biases reported by Das et al. (1998) and Lim (2001) who find that forecast biases increase for companies with greater informational uncertainty.

(iii) Optimal Reaction to News

Here we report the results of estimating equations (4) through (6) using both measures of news as the explanatory variables on the RHS.[9] When reporting our results, we only report the values of the combined coefficients to facilitate easy comprehension. As before, our intention is to detect any changes in analysts' forecast efficiency, now viewed as their reaction to news, during the crisis period. Regardless, it is informative to make some general observations of analysts overall efficiency in the main sample first. Table 4 documents the results of the model which uses prior-year earnings change, PERF_{t-1}, as a surrogate for earnings news.

All three regression models, presented for the main sample in Table 4, are significant at better than 0.01. Significance of the actual model ($R^2 = 0.151$, $F = 21.101$) shows that prior-year earnings change is useful in explaining the current year earnings change. Analysts themselves also do utilise the information in prior-year earnings change when making predictions, as shown by the significance of the forecasted change model ($R^2 = 0.508$, $F = 123.050$). However, the significance of the forecast error model ($R^2 = 0.057$, $F = 7.141$) suggests that analysts incorporate the available information *incorrectly* into their forecasts.

Studying the combined coefficients next, we focus our attention on the first and fourth columns of Table 4, which describes the impact of low prior-year performance. For the actual change model (fourth column), we observe insignificant intercept and slope coefficients, -0.006 ($t = -1.271$), and -0.027 ($t = -0.443$) respectively, telling us that low prior-year earnings change has no influence on current year's earnings change. However, analysts wrongly assume that low prior-year performance positively impacts current year earnings. This is shown in the first column where the analysts' determined slope is -0.261 ($t = -9.017$). Within the low performers, 96% of them have negatively signed prior-year earnings change. This implies that in the face of negative prior earnings change, analysts erroneously assume that the next year's earnings would be reversed.[10] Finally, we look at the difference between the forecasted and actual earnings model to quantify the error. The slope coefficient from the seventh column is significantly positive at 0.235 ($t = 3.918$). This indicates that analysts overestimate the positive effect of low prior performance on current year earnings, an under-reaction to negative news.

Table 4

Earnings Change and Forecast Error Regressed on Prior-year Earnings Change

$$\text{The Model (RHS)} = \alpha_0 + \alpha_1 \text{LOPERF}_{t-1} + \alpha_2 \text{HIPERF}_{t-1} + \alpha_3 \text{PERF}_{t-1} + \alpha_4(\text{PERF}_{t-1} \times \text{LOPERF}_{t-1}) + \alpha_5(\text{PERF}_{t-1} \times \text{HIPERF}_{t-1}) + \varepsilon_t$$

	Dependent Variable								
	$\frac{(F_t^{t-1}-E_{t-1})}{P}$ *Forecasted EPS Change*			$\frac{(E_t-E_{t-1})}{P}$ *Actual EPS Change*			$\frac{(E_t-F_t^{t-1})}{P}$ *Forecast Error*		
	(1) Low	*(2) Normal*	*(3) High*	*(4) Low*	*(5) Normal*	*(6) High*	*(7) Low*	*(8) Normal*	*(9) High*
Intercept	**0.012****	**0.007****	**0.026****	**−0.006**	**−0.004**	**0.022****	**−0.018****	**−0.011****	**−0.004**
	(5.245)	(4.613)	(10.735)	(−1.271)	(−1.319)	(4.344)	(−3.818)	(−3.561)	(−0.823)
Slope	**−0.261****	**−0.022**	**−0.757****	**−0.027**	**0.499**	**−0.739****	**0.235****	**0.521**	**0.018**
	(−9.017)	(−0.146)	(−21.573)	(−0.443)	(1.611)	(−10.128)	(3.918)	(1.692)	(0.250)
R^2	0.508 ($F = 123.050$**)			0.151 ($F = 21.101$**)			0.057 ($F = 7.141$**)		

Notes:
The sample consists of 601 firm-year observations that had eight-month ahead forecasts of annual earnings and at least six consecutive years of actual annual earnings available from I/B/E/S. Raw prior-year earnings information is classified as low, normal or high based on the magnitude of prior-year earnings change. Combined intercept and slope coefficients are reported. t-statistics are reported in parentheses below the coefficient estimates. ** and * indicates that the coefficient is significantly different from zero at the 0.01 and 0.05 levels respectively.

E_t = Actual year t earnings.
F_t^{t-1} = Forecast of year t earnings made 8 months prior to year-end.
P = Stock price at time of forecast.
PERF_{t-1} = The prior-year earnings change ($E_{t-1} - E_{t-2}$) scaled by the concurrent price at year $t-1$.
LOPERF_{t-1} and HIPERF_{t-1} are dummy variables coded as '1' if PERF_{t-1} is in the lower/upper quartile in that year, and coded '0' if otherwise.

Over or under-reaction is, however, absent when we compare the forecasted and actual earnings models for high prior-year performance. We look at the sixth column and observe that the intercept and slope for the actual change model are 0.022 ($t = 4.344$) and -0.739 ($t = -10.128$) respectively. The negative slope indicates that a stronger prior-year performance is reversed in the following year. The forecasted earnings model in column three shows similarly signed coefficients. Consequently, the difference between the forecasted and the actual model is not significant as given in column nine (intercept: -0.004, $t = -0.823$; slope: 0.018, $t = 0.250$). Analysts appear to react optimally to news for firms with high prior-year performance.

Finally, we observe the impact of normal levels of performance by centring our attention on the second and fifth columns. Almost all the coefficients are insignificant. Thus we observe from column eight that there is little difference between analysts' determined and actual slope coefficients, suggesting that analysts also do not over or under-react in response to non-informative levels of prior-year performance. Based on the results from the main sample, we observe that though analysts do not under or over-react to high prior-year earnings change, they under-react to low prior-year earnings change. We next investigate whether this main sample result is driven by analyst behaviour during the crisis period.

The pre and post-crisis regressions presented in Table 5 tells a story consistent with our earlier findings from the first two notions of efficiency. First, we focus on the pre-crisis sub sample reported in Panel A. From the significance of the actual earnings change model ($R^2 = 0.619$, $F = 158.319$), we see that PERF_{t-1} is useful in explaining actual current earnings change before the crisis. Analysts also utilise this information when forecasting earnings change ($R^2 = 0.256$, $F = 33.597$). However, the results of the forecast error model indicate that analysts are efficient in incorporating the information in prior-year earnings into their forecasts ($R^2 = 0.008$, $F = 0.785$). Looking at column seven to nine, we observe that all the slope coefficients are insignificant, consistent with the low explanatory nature of the regression. This means that regardless of the nature of prior performance, analysts' incorporate this information into their forecasts efficiently, without under or over-reaction.

Table 5

Sub-sample Analysis: Earnings Change and Forecast Error Regressed on Prior-year Earnings Change

$$\text{The Model (RHS)} = \alpha_0 + \alpha_1 \text{LOPERF}_{t-1} + \alpha_2 \text{HIPERF}_{t-1} + \alpha_3 \text{PERF}_{t-1} + \alpha_4(\text{PERF}_{t-1} \times \text{LOPERF}_{t-1}) + \alpha_5(\text{PERF}_{t-1} \times \text{HIPERF}_{t-1}) + \varepsilon_t$$

	Dependent Variable								
	$\frac{(F_t^{t-1}-E_{t-1})}{P}$ *Forecasted EPS Change*			$\frac{(E_t-E_{t-1})}{P}$ *Actual EPS Change*			$\frac{(E_t-F_t^{t-1})}{P}$ *Forecast Error*		
	(1) Low	*(2) Normal*	*(3) High*	*(4) Low*	*(5) Normal*	*(6) High*	*(7) Low*	*(8) Normal*	*(9) High*
Panel A: Pre-crisis Sample Period									
Intercept	**0.016****	**0.006****	**0.030****	**0.006**	**−0.000**	**0.029****	**−0.010****	**−0.006***	**−0.000**
	(7.886)	(4.059)	(13.812)	(1.356)	(−0.001)	(6.398)	(−2.630)	(−2.142)	(−0.069)
Slope	**−0.034**	**0.096**	**−0.783****	**−0.071**	**0.291**	**−0.785****	**−0.038**	**0.196**	**−0.002**
	(−1.251)	(0.529)	(−27.202)	(−1.240)	(0.752)	(−12.749)	(−0.739)	(0.570)	(−0.036)
R^2	0.619 ($F=158.319$**)			0.256 ($F=33.597$**)			0.008 ($F=0.785$)		
Panel B: Post-crisis Sample Period									
Intercept	**−0.013****	**0.009****	**0.004****	**−0.084****	**−0.022**	**−0.029**	**−0.071****	**−0.031****	**−0.032**
	(−2.087)	(2.246)	(0.652)	(−4.553)	(−1.684)	(−1.583)	(−3.739)	(−2.334)	(−1.734)
Slope	**−0.914****	**0.142**	**−0.316**	**−0.250**	**−0.254**	**0.100**	**0.664****	**−0.397**	**0.416**
	(−15.692)	(0.547)	(−1.651)	(−1.398)	(−0.319)	(0.170)	(3.592)	(−0.480)	(0.684)
R^2	0.763 ($F=64.922$**)			0.090 ($F=1.998$)			0.295 ($F=8.465$**)		

Notes:
The pre-crisis sample of 494 observations and the post-crisis sample of 107 observations are used in this model in Panels A and B respectively. Only month-end forecasts made after 2 July, 1997, are considered in the post-crisis sample. Raw prior-year earnings information is classified as low, normal or high based on the magnitude of prior-year earnings change, PERF_{t-1}. Combined intercept and slope coefficients are reported. t-statistics are reported in parentheses below the coefficient estimates. ** and * indicates that the coefficient is significantly different from zero at the 0.01 and 0.05 levels respectively.

Turning our attention to the post-crisis period (Panel B of Table 5), we first note that the actual earnings change regression model is insignificant ($R^2 = 0.090$, $F = 1.998$). This lack of relationship has come about only after the crisis. Our pre-crisis sub-sample had an explanatory regression ($R^2 = 0.256$, $F = 33.597$), implying that prior performance of companies had some permanent impact on subsequent year's earnings. But during the crisis, the firm's prior performance, no matter how good or bad, did not impact subsequent year's earnings changes. However, the high significance and R^2 of the forecasted earnings model ($R^2 = 0.763$, $F = 64.922$) show that analysts mistakenly assumed a relationship, hence causing their forecasts to be biased ($R^2 = 0.295$, $F = 8.465$). From the forecasts error model (columns seven to nine), we find evidence of under-reaction to low prior performance. The slope coefficient in column seven is significantly positive (0.664, $t = 3.592$), showing that analysts under-reacted to bad news.

We repeat the above analyses from Tables 4 and 5 with a more refined proxy for news – *unexpected* prior-year earnings change. The resulting coefficients (unreported) closely resemble those reported for the previously employed proxy, and thus corroborate our conclusions. We also conduct an additional robustness test (not reported) that involves reclassification of high and low performance companies as extreme deciles instead of quartiles. If firms in the lowest performance decile suffered more from the inefficiencies documented earlier for the lowest performance quartile, this new classification would strengthen the significance of our key results. If, instead, the observed inefficiencies exist across the entire low performance quartile, then demarcating only the last decile as low performers should weaken our key results. This is because some of the observations previously classified as low performance will now be regarded as normal, and our statistical tests that compare extreme groups to 'normal' groups would be less powerful. Upon implementation, we document evidence for the latter scenario – the significance level of the post-crisis under-reaction to bad news, defined by PERF_{t-1} (UPERF_{t-1}), reduces to about 0.13 (0.09). This suggests that the previously observed under-reaction to bad news exists across the entire extreme quartile of low performance firms.

To sum up, we find no evidence of inefficiency in analysts' reaction to prior-year earnings information in the pre-crisis period. The under-reaction to bad news uncovered in the main sample is due to analysts not fully incorporating negative information during the crisis period. Our results point to a structural change, after the onset of the crisis, in analysts' ability to react optimally to news. In particular, their under-reaction to bad news during the crisis appears consistent with Daniel et al.'s (1998) model in which market agents are over confident and exhibit biased self-attribution. The model posits that these agents believe too strongly in their own private information and attach too little significance to public information. Analysts' under-reaction to publicly available negative news, like the onset of the crisis, is a possible manifestation of this theoretical model.

4. CONCLUSION

This paper examines the efficiency of analysts' forecasts in Singapore. While analysts' forecasts before the crisis can be described as efficient, the forecasts made during the crisis period contained systematic biases. During this period, analysts were systematically optimistic, forecasted earnings changes that exceeded actual changes, and did not fully incorporate negative earnings-related news. Interestingly, increased uncertainty and poor recent performance, the two factors uncovered by the existing literature to be associated with increased biases in the cross-section of analysts' forecasts, also appear to be related to an increase in such biases during the crisis period. We conjecture that such a temporal increase in forecast biases could be due to behavioural factors. Our results, indeed, appear to support recent models of behavioural finance in which significant changes in market sentiment lead to structural breaks in the behaviour of market participants (Barberis, Shleifer and Vishny, 1998; and Brown and Cliff, 1999).

De Bondt and Thaler (1990) argue that analyses of analysts' forecasts are important, as the rationality of analysts is likely to be an upper bound for the rationality of the less sophisticated common investors. Our results suggest that professional security analysts, arguably amongst the most astute of market participants, exhibit systematic biases in forming their expectations during periods of heightened economic uncertainty. This calls into question the classical assumption about the rationality of the marginal investor.

NOTES

1 In contrast, managers of companies with good news have every incentive to push this news out to investors as fast as possible (Lang and Lundholm, 1993).

2 More specifically, Das et al. (1998) and Lim (2001) use forecast data from the US and find that various proxies for the richness of a company's information environment, such as historical earnings variability, standard deviation of weekly excess stock returns and market capitalisation, are inversely related to forecast bias.

3 Economies that have been enjoying buoyant growth, like those in Southeast Asia, were dragged backwards by the far-reaching effects of this crisis. For the ten years prior to the crisis, countries like Malaysia, Indonesia and Singapore had enjoyed real year-on-year GDP growth averaging 9.1%, 6.9%, and 2.9% respectively. These figures dropped to −9.9%, −13.25%, and 0.9% respectively during the two years (1998 and 1999) of the crisis. The effects on corporate profits were even starker. For the same countries, average corporate profits during the two crisis years were, respectively, 943%, 84%, and 43% lower than those of the pre crisis year of 1996. Unemployment levels, compared with those in the previous decade, rose between 1–2% for most countries in Southeast Asia. Stock markets were not unscathed – dropping between 45–74% at their lowest points. Data utilised to obtain the above numbers are from the following sources: Datastream (stock market movements and GDP), Asian Development Bank's key indicators of developing Asian and Pacific countries, volume 32, 2001 (Unemployment), and the Osiris database (corporate profits).

4 From I/B/E/S's Asia-Pacific data population summary statistics, we observe that amongst the Southeast Asian countries – Indonesia, Philippines, Thailand, Malaysia and Singapore – the latter two have the highest number of companies covered by I/B/E/S (close to 200 as of August 2000). However, Malaysia is generally regarded as a relatively more closed economy. This concern is accentuated by her government's implementation of capital controls restricting financial flows in and out of the country at the height of the crisis in September 1998.

5 This notion of forecasts efficiency corresponds most closely to the definition of informational efficiency of asset prices.

6 Prior literature suggests two additional proxies for earnings-relevant news. Easterwood and Nutt (1999) propose the use of prior-year forecast error (earnings surprise) as a proxy for news, whereas Amir and Ganzach (1998) argue that prior-year forecast revision serves as a better surrogate for earnings related news. Since the use of these proxies necessitates a 2-year ahead forecast of year *t*'s earnings, we do not perform the pre and post-crisis analysis with these proxies as it would shrink the already small crisis sample. However, we do perform total sample analyses using

prior-year forecast errors and prior-year forecast revisions as proxy for news. The unreported results are qualitatively similar to main sample analyses using $PERF_{t-1}$ and $UPERF_{t-1}$.

7 O'Brien's (1988) conclusions are based on the time period 1975 to 1982. Since then, and especially in the 1990s, the lag period between an analyst's revision and its inclusion in the I/B/E/S consensus has been greatly reduced (I/B/E/S Research Bibliography, 1995; and Keane and Runkle, 1998). Therefore our eight-month ahead measure is unlikely to suffer much from such flaws.

8 We use the Osiris database, which provides specific company accounts data such as the geographical breakdown of sales for listed firms. The average figure of 83.2% is estimated by examining individually the main sample's top 30 represented firms, which together make up the majority of all firm-year observations of our main sample. The high percentage implies that a substantial fraction of the sales of our sample's firms is generated in Asia.

9 Like Abarbanell and Bernard (1992), Easterwood and Nutt (1999) estimated their models using OLS. We follow their methodology, bearing in mind that the estimated coefficients should be interpreted with some caution since the *t*-stat may be overstated because of possible cross sectional dependence in the data (across firms) (Bernard, 1987).

10 This seemingly counter intuitive result was also found by Easterwood and Nutt (1999).

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